# MODEL BASED FAULT DETECTION FOR SAFETY MANAGEMENT OF THE INDUSTRIAL PROCESSES

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**Abstract.** *Detection and diagnosis are important actions offered by the complex automations, that contribute to keeping the exploitation of the process safe. The paper presents a efficient detection solution concepts based on the dependency and the causal connections that exist between the process parameters and proposes techniques and algorithms for the safe evolution of the process. The variables of these connections are specified from the a-priori knowledge on the process. To detect the process faults, the paper proposes a method based on analytical redundance evaluation and on computing residues, using the measurements collected from the process and on the mathematical models associated to the process. This approach is recommended of the modern supervision and optimization systems, for the industrial processes.*

**Abstract.** *Detecția și diagnoza sunt acțiuni importante atribuite automatizărilor complexe, care asigura menținerea exploatării procesului în siguranță. Lucrarea prezinta o soluție eficienta de detecție a defectelor bazata pe dependența și conexiunile cauzale care există între parametrii procesului și propune tehnici și algoritmi pentru evoluția în siguranță a procesului. Variabilele acestor conexiuni sunt specificate din cunoștințele a priori despre proces. Pentru a detecta defectele din proces, lucrarea propune o metodă bazată pe evaluarea redundantei analitice si pe calculul reziduurilor estimate prin măsurători colectate din proces folosind modele matematice asociate funcționarii procesului. Această abordare este recomandată de sistemele moderne pentru supervizarea si conducerea optimala a proceselor industriale.*

**Keywords:** process security, faults detection, model-based fault detection; analytical redundancy, fault residues indicator.

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## 1. Introduction

The detection and diagnosis of systems is a problem with a wide degree of complexity: abnormal, suspicious or dangerous conditions must be detected, then the cause must be determined and finally, the action to remove the cause must be decided. In the context of surveillance and diagnosis, the data used, presents distortions due to a number of causes, such as: the imprecision of the acquisition equipment, the measurement noise induced by the environment in which the data source evolves, the possible failures of the sensors and execution elements, the

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analog or digital inhomogeneity, etc.[1],[2].This problem is managed by the supervisory and decision level in a hierarchical control configuration. [3],[4],[5],[28],[30].

The objective of the supervision level is to guarantee the safety and protection of the process through modern techniques for the detection and diagnosis of failure states. The paper [10] proposes a global estimation of the techniques for the evaluation of defects through fault trees, coherent with the mechatronic vision of R. Iserman, [11], [12].

In the papers [15], [17], [18], a systematic analysis of the performance of detection and diagnosis algorithms using fault trees is presented. This simultaneously provides an estimate of the safety of the supervised system and an analysis of the rate of false alarms and unreported faults, consequences which are explicitly modeled in the diagnosis algorithm.

However, the measured data carries a certain amount of information that can be exploited to fail to diagnose the source that generated them. Thus, analytical models of normal or abnormal behavior can be built, generally based on the statistical characteristics of the measured values in the processes, on a statistic
of defects and abnormal behavior. To decode the information regarding defects, different reasoning is used. Thus, two directions are distinguished depending on the logic used in these reasonings:
a) a direction that consists of using abnormal information to aid the data on defects and their symptoms.
b) another direction based on coherence, which starts from the information from the structure of the elements and their normal functioning, in order to locate the errors in relation to reference behavior.

The diagnosis therefore requires not only the definition of the normal functioning state, but also information about abnormal scenarios. Different techniques are available to handle both numerical and symbolic observations, as well as knowledge regarding the application of physical principles or heuristic knowledge.

The main objective of a detection system is either to move directly to the recognition of defects after the action is taken, or to move from a normal operating model to the recognition of the defect, and then to take action. In the event of an abnormal evolution of a system, detection means looking for the cause of the malfunction, using knowledge related to the structure of the system, its possible malfunctions and the available observations.

There are several methods for detecting defects in the abnormal operation of a process, from monitoring and signaling the exceeding of the normal limits of the technological parameter values, [9], [25] techniques, to techniques based on

functional redundancy, residue theory and Artificial Intelligence techniques, [27], [31], [32].

In practice, the most commonly used diagnostic method is to monitor the level or trend of a particular signal and take action when the signal has reached a given threshold. This method of checking the limit, even if it is simple to implement, has some drawbacks. The first negative aspect is the possibility of false positive alarms in the event of the presence of noise, variations in the input or change of the operating point. The second negative aspect is that a single defect can lead to several signals in the system to exceed their limit values and appear as multiple defects, thus making it difficult to isolate the defect.

In order to avoid these shortcomings, the concept of analytical redundancy is introduced, which uses the mathematical model of the monitored process, a concept which is also known as model-based fault detection. The major advantage of the model-based approach is given by the fact that there is no longer the need for additional hardware equipment to implement a fault detection algorithm, which is implemented in software together with the system management and control algorithm.

## 2. Model-based detection technique

Model-based detection can be defined as the determination of the defects of a system by comparing the measurements available in the process with a-priori information represented by the mathematical model of the process, generating residual quantities and estimating them.

The overall structure of a model-based fault detection system is illustrated in Fig. 1 and comprises of two main components: waste generation and decision making. This configuration structure can by suggested and is now widely accepted in the systems detection and diagnostic engineering scientific community.

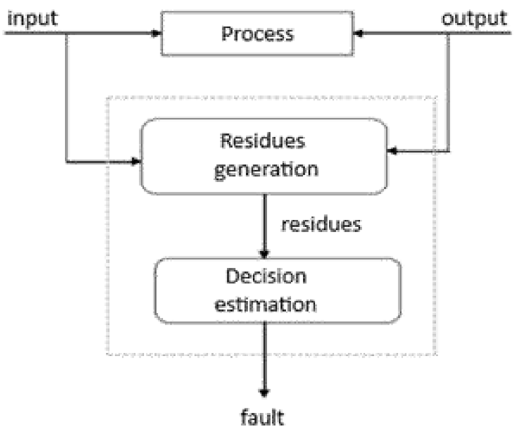


**Figure 1.** Model-based fault detection diagram.

The purpose of this residue module is to generate a fault indicator signal called residue, using the available input and output information from the monitored process. This signal is designed to reflect the existence of a defect in the analyzed system. The residue should normally be zero when no defect is present in the system, but significantly different from zero when a defect occurs. This means that the residue has the characteristic property of being independent of the system inputs and outputs under ideal conditions. The algorithm or digital processor used to generate the residuals is called *the residue generator*.

In the decision module, residues are examined to check the probability of defect and a decision rule is applied to determine whether certain defects have occurred. The decision-making process may consist of a simple threshold test on instantaneous values or on slippery residue media, or it may consist of statistical methods.

In many applications of the process safe operation, model-based detection techniques are proposed. These mechanisms used for detecting defects rely on comparing the available measurements from the process with a priori information obtained from mathematical models of operation associated with the process. The differences found generate residual quantities or residues that decide on the existence of defects. [3],[20],[27],[29],[30].

The major advantage of this approach is that no additional hardware equipment is required for the software implementation of the detection algorithm, this being based on the resources offered by the process automation system, [28], [29]. Parameters associated with the process operation are introduced into an additional set of linearly independent parity equations to generate the parity vector or residual vector. Thus, through this operation, the extended set of process equations (parity equations) can be determined and the residuals for fault detection can be calculated.

When the system has all kinds of possible defects, caused by sensors, process components and execution elements, the system model described by the state equations, is of the following form:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Bf_e(t) + f_c(t) \\ y(t) = Cx(t) + Du(t) + Df_e(t) + f_s(t) \end{cases}, \forall\, t \in \mathbb{R}_+ \tag{1}$$

,

where **u** is the system input, **x** is the vector state, **y** is the system output, and the vectors $\mathbf{f_s}$, $\mathbf{f_c}$, $\mathbf{f_e}$ represent the defect vectors for the sensors, process components and execution elements, respectively.

The no fault state is determined by the equations: r(t)=0 or f(t)=0.[3],[4],[6],[11].

## 3. Case study

To illustrate the use of the algorithm described above and to present the results of applying this algorithm on a numerical example, we propose a thermo-energetic process generically described by a model expressed by stationary balance equations in which the terms of the equations, are expressed by thermo-energetic parameters p, specific to the process [17], [24], [25],[37]:

$$\begin{aligned}
&(1): \quad p_1+p_2-p_3=0\\
&(2): \quad p_3+p_4-p_5=0\\
&(3): \quad p_5+p_6-p_2-p_7=0\\
&(4): \quad p_7-p_8-p_9=0
\end{aligned} \tag{2}$$

Since the variables in the process are technologically interdependent, additional (parity) equations are generated between the variables, in order to obtain analytical redundancy and thus determine the extended set of linear combinations of the process equations (parity equations).

By numbering each of the equations identified in (1) from 1 to 4, we obtain the extended set of equations:

*(1+2),(1+3),(2+3),(3+4),(1+2+3),(1+3+4),(2+3+4),(1+2+3+4).*

were,

$$\begin{aligned}
&(1+2): \; p_1+p_2+p_4-p_5=0\\
&(1+3): \; p_1-p_3+p_5+p_6-p_7=0\\
&(2+3): \; p_3+p_4+p_6-p_2-p_7=0\\
&(3+4): \; p_5+p_6-p_2-p_8-p_9=0\\
&(1+2+3): \; p_3+p_4+p_6-p_7=p_1-p_3\\
&(1+3+4): p_1-p_3+p_5+p_6-p_8-p_9=0\\
&(2+3+4): p_3+p_4+p_6-p_2-p_8-p_9=0\\
&(1+2+3+4): p_1+p_4+p_6-p_8-p_9=0
\end{aligned} \tag{3}$$

The corresponding measurements presented in the following Table 1 are associated with the parity equations of the extended model:

**Table 1.** Process measured data

| | $p_1$ | $p_2$ | $p_3$ | $p_4$ | $p_5$ | $p_6$ | $p_7$ | $p_8$ | $p_9$ |
|---|---|---|---|---|---|---|---|---|---|
| Value | 111.3 | 18.2 | 191.4 | 23.8 | 148.7 | 13.6 | 181.2 | 106.4 | 39.7 |

By substituting each variable in the model equations with the measured values, the residuals associated with the parity equations are calculated. A predetermined evaluation threshold is imposed (in this example at the imposed for example value equal to 2.0, to decide on the status of the parameters.

The comparative results between the calculated residual values and the imposed threshold are presented in Table 2.

In this table, the first line represents the parity equation numbering, and the second provides the result of the equation-measurement comparison. The meaning of the elements in the second line is "A" – for abnormal residue with a value exceeding the imposed threshold and "N" - normal residue with a value below the threshold.

**Table 2.** Model residue classification

| | **1** | **2** | **3** | **4** | **1+2** | **1+3** | **2+3** | **3+4** | **1+2+3** | **1+3+4** | **2+3+4** | **1+2+3+4** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Status | A | A | A | A | N | A | A | N | A | A | A | N |

The analysis of the residuals on the extended set of equations in (1), shows that the residual values are below the threshold for the combinations (1+2), (3+4) and (1+2+3+4). It results that the respective equations are respected and therefore the variables $p_1$, $p_2$, $p_4$, $p_5$, $p_6$, $p_8$ and $p_9$ that define these equations are not in a fault state and consequently the variables $p_3$ and $p_7$ are the faults. If the vector p is known, the cause sources can be evaluated by diagnostic techniques. [19], [ 38].

## 4. Conclusions

- The paper proposes an efficient methodology based on detection techniques assigned to a structure organized on automation levels for control and decision making that provides the process with efficiency and operational safety of an industrial process.
- In cases of near failure, the decision-making supervisor level ensures, in addition to optimizing the process, the development and application of appropriate strategies and measures for detecting failures, locating causes and remedying defects that occur in the process.
- Fault conditions may occur due to damage to technological components or degradation of components in the automation system and are highlighted based on information collected from real-time operation of the process.

- The paper deals with new aspects and concepts for highlighting abnormal operating regimes, through efficient detection techniques and methods, a necessary step in the diagnosis process of the fault causes.
- For the evaluation of failure states, the model-based detection method is proposed. This approach can estimate the defects of a process control system by comparing the measurements available with a priori information from the mathematical model of the system, to generate residual quantities. A residue is a fault indicator of the abnormal status or the correct functioning of the monitored systems.

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